APRIL 27, 2020

COUPLING LAND-USE MODELS AND NETWORK-FLOW MODELS

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Project ID#: eems035
Pillar(s): Urban Science

Energy Efficient Mobility Systems (EEMS)
Vehicle Technologies Office
U.S. Department of Energy

OVERVIEW

Timeline

- Start date: 10/2017
- End date: 09/2019
- Percent complete: 100%

Budget

- Total funding: $0.69M
  - DOE share: 100%
- FY 2018: $0.26M
- FY 2019: $0.43M

Barriers

- Transportation planning overlooks long-term impacts on urban development, induced travel demand
- Computationally expensive transport models undermine long-term analysis
- Impact of new mobility technologies on long term household choices uncertain

Partners

- Project Lead: LBNL
- Partners: LBNL, NREL, ORNL, INL, ANL
- Collaborators: Google, Purdue, MTC

RELEVANCE AND OBJECTIVES

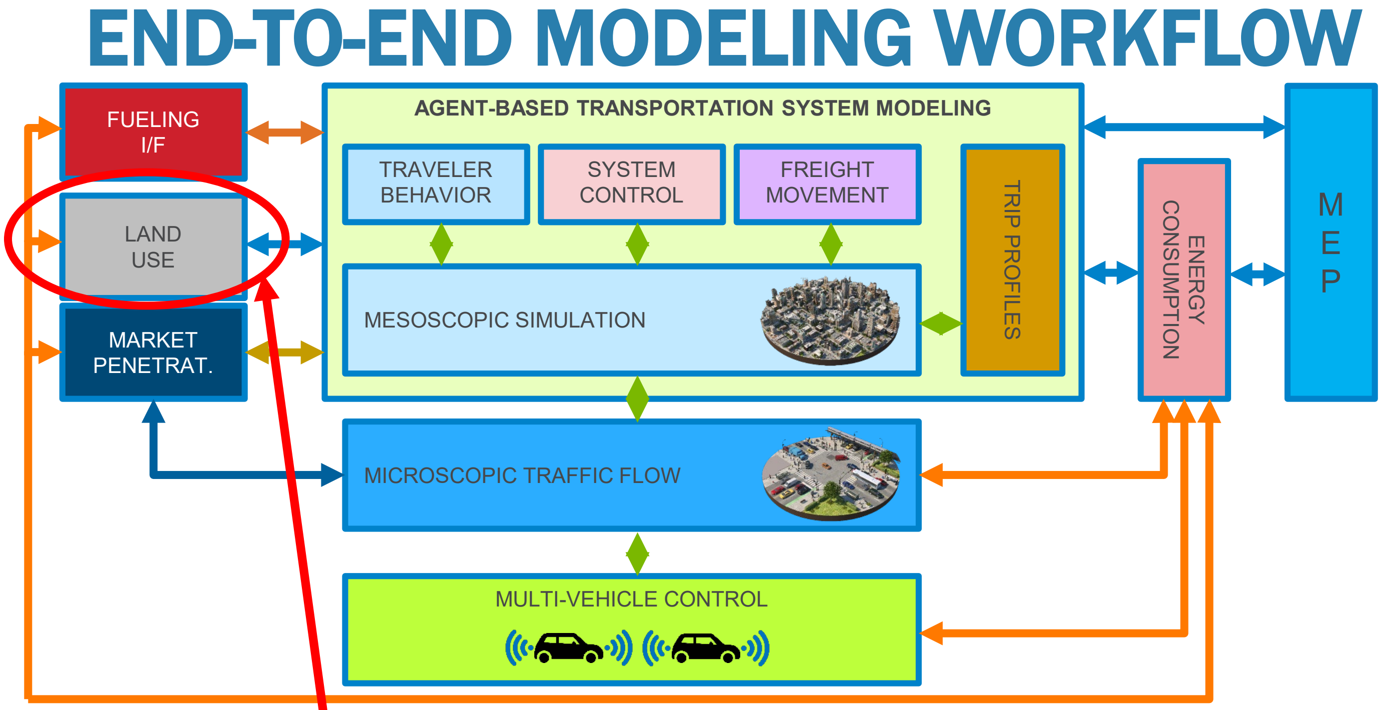
- Need to quantify the impact of urban development on mobility patterns and energy use
- Need to quantify the impacts of SMART technologies on long-term urban development
- Need to evaluate combined policy impacts of land use and transportation to avoid endogeneity bias
- Supports EEMs/VTO Goal: Linking long-term modality styles with short/medium term mode choice in a multimodal transportation system, with the ability to simulate emerging mobility services.

- Develop an integrated modeling pipeline that encompasses land use, travel demand, traffic assignment, and energy consumption
- Model combined and cumulative impacts of transportation infrastructure and land use
- Improve computational performance to simulate regions over 30 years for scenario analysis

MILESTONES

Date	Milestone	Status
September 2018	Initial implementation of ActivitySynth (daily activity demand generation for mandatory trips)	Complete
March 2019	Performance evaluation of integrated modeling platform, identify opportunities for improvement of computational efficiency and predictive power.	Complete
June 2019	Progress measure: Run UrbanSim and BEAM end-to-end on 2+ scenarios in Bay Area and produce a portfolio of MEP metrics	Complete
September 2019	Evaluate implementation of the platform for potential application to additional metro areas (e.g. Austin, Detroit).	Complete
December 2019	Replaced ActivitySynth with a complete Activity Based Model ActivitySim, developed in collaboration with MPOs	Complete
March 2020	Benchmarked and Validated ActivitySim and MicroSim	Complete

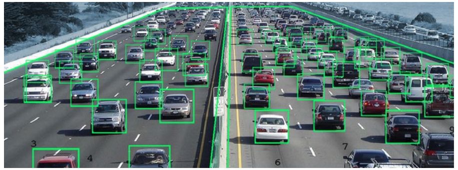
APPROACH



UrbanSim is the *only* land use model in the SMART Mobility workflow and is thus path-critical for most core models

APPROACH

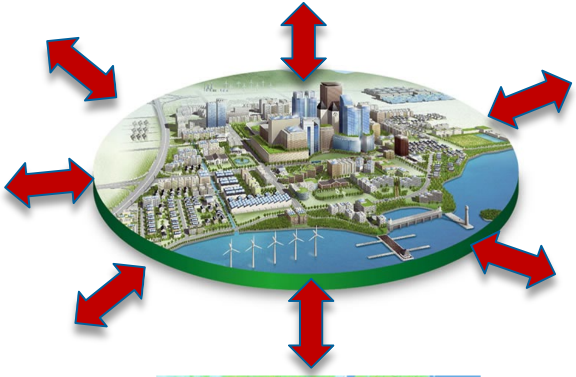
New Forms of Mobility



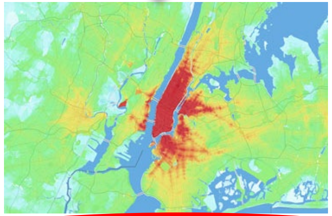
Enhanced Traffic Flow

Vehicle Ownership / Vehicle Energy Performance

Traveler Behavior



Charging Siting & Operations

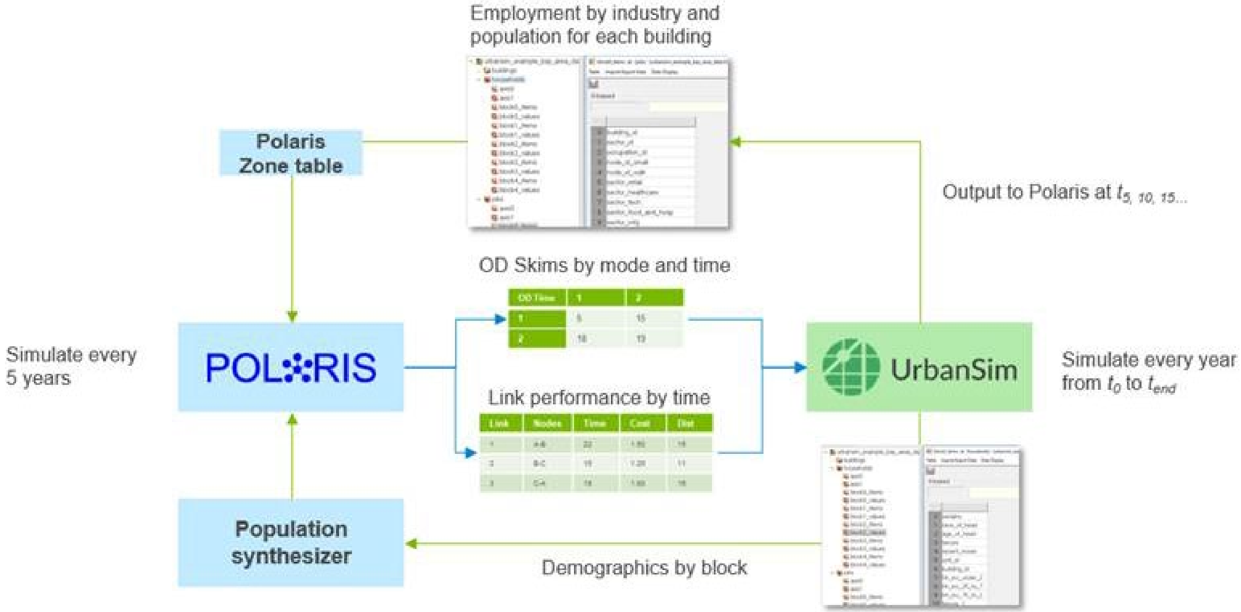


Advanced Accessibility Analysis

Land Use Change

TECHNICAL ACCOMPLISHMENTS

UrbanSim + POLARIS Workflow

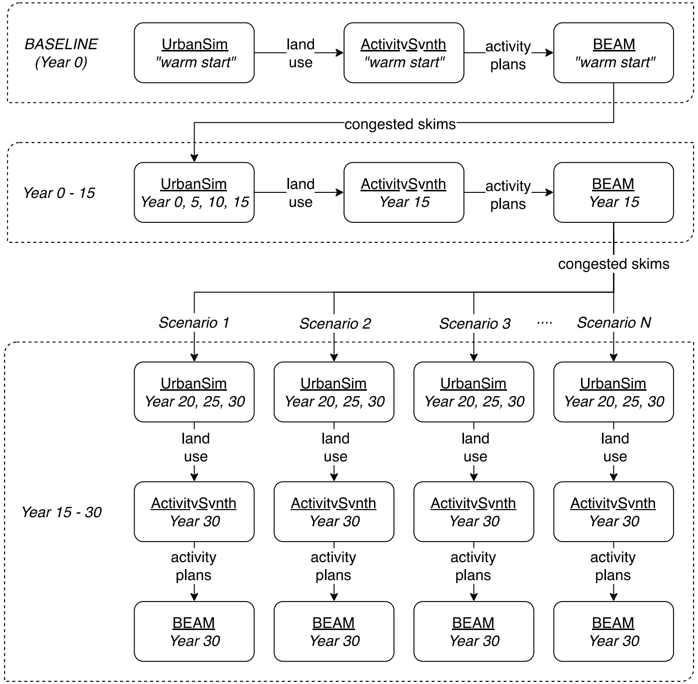


- **Workplace location choices, activity demand generation handled by travel model (POLARIS)**

TECHNICAL ACCOMPLISHMENTS

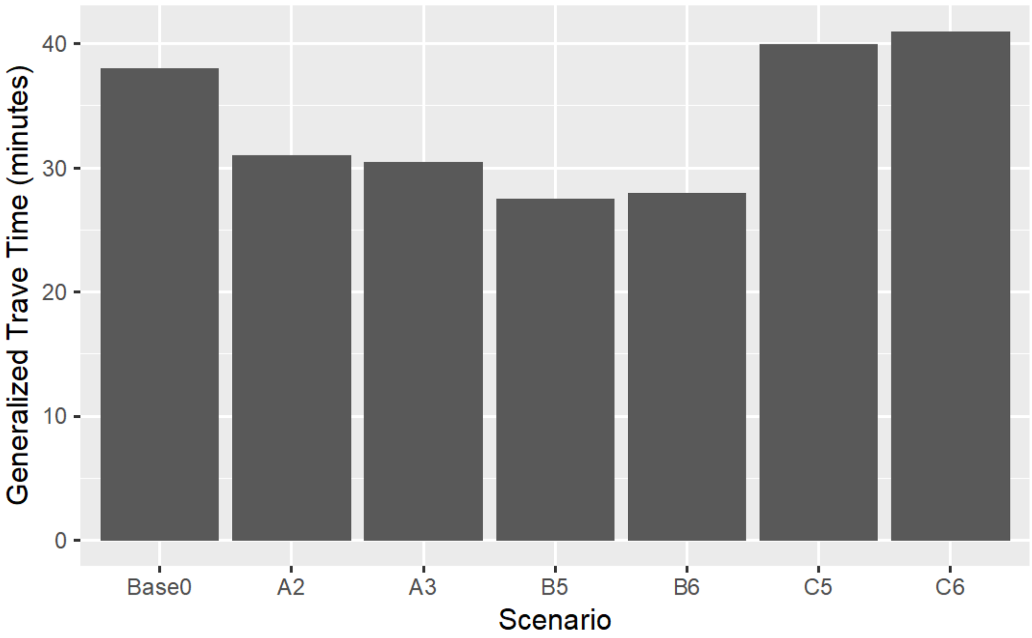
UrbanSim + BEAM Workflow

- Workplace location choices, activity demand generation handled by land use models (UrbanSim + ActivitySynth)



URBANSIM + BEAM RESULTS

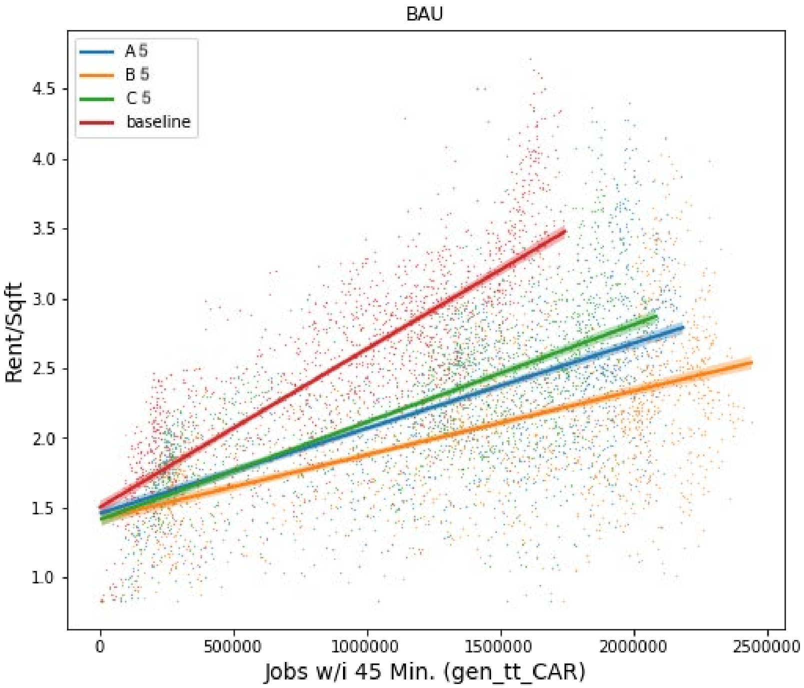
Average (generalized) commute times by scenario

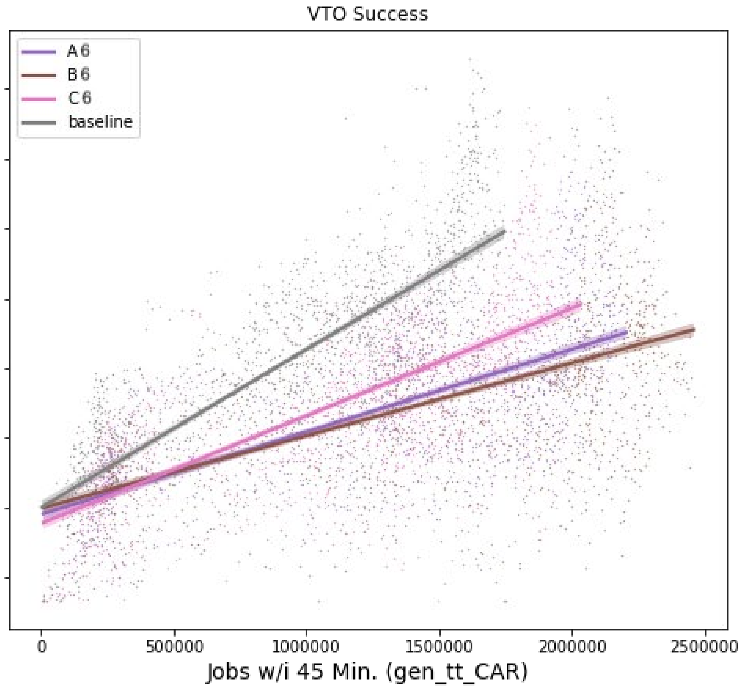


- Reliance on high-cost modes in Scenario B, such as transit and ride-hailing, lead to a downward pressure on commute times
- Accessibility gradients show how this trend translates into changes in built environment

URBANSIM + BEAM RESULTS

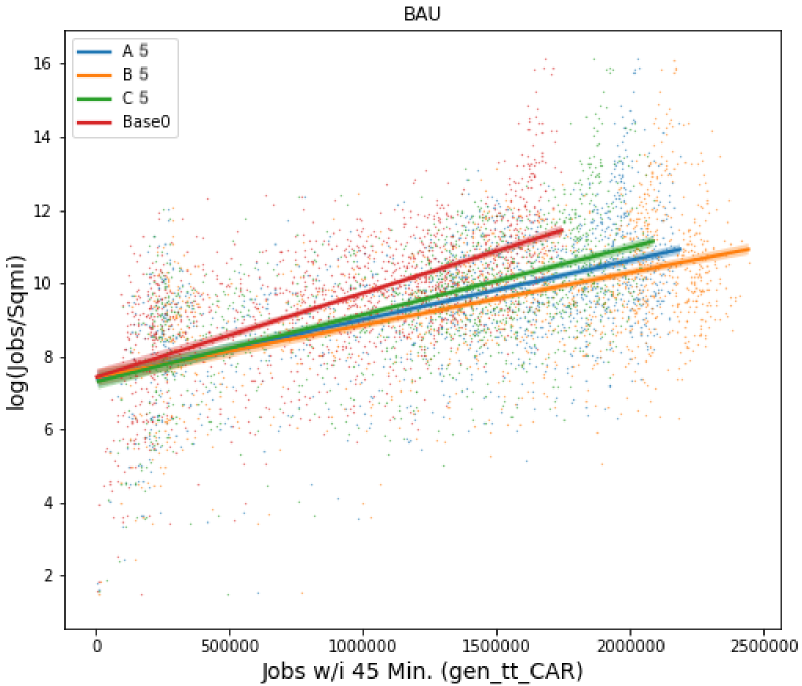
Decentralized jobs-accessibility vs. rent gradients

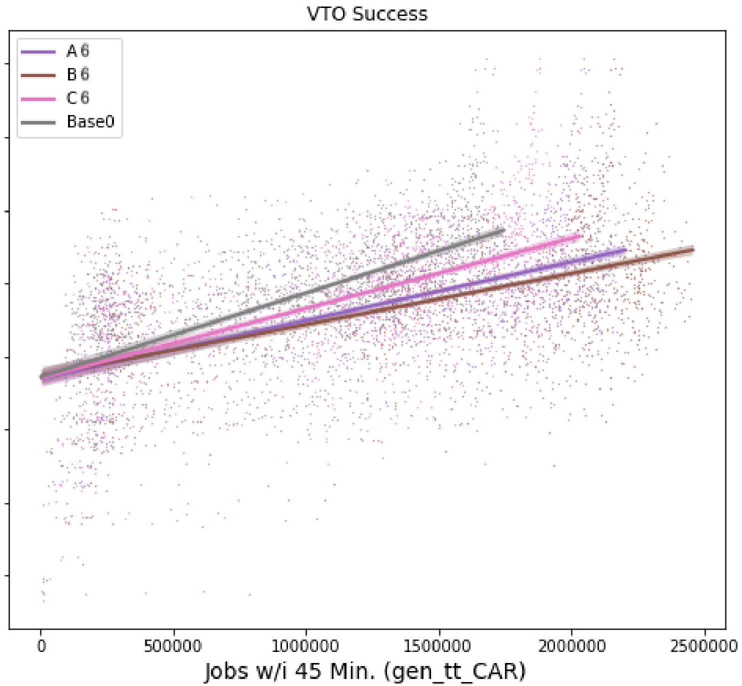




URBANSIM + BEAM RESULTS

Decentralized jobs-accessibility vs. jobs density gradients





TECHNICAL ACCOMPLISHMENTS

UrbanSim + ActivitySim Workflow

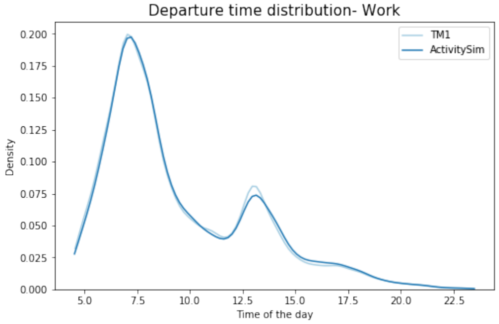
- BEAM requires person-level activity plans as an input
- UrbanSim does not currently produce these
- ActivitySim is a set of 27 models
  - Work/School location
  - Coordinated daily activity Pattern
  - Mandatory, Non-mandatory and joint tours and trips
  - Frequency, destination, schedule and mode choice

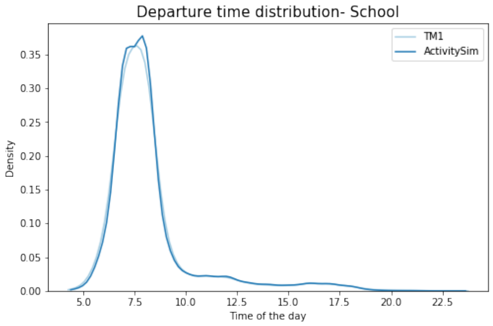
~25 million trips
Initial validation completed
Run time is approximately 1 hour (24 cores machine) with 100% of population and no sampling

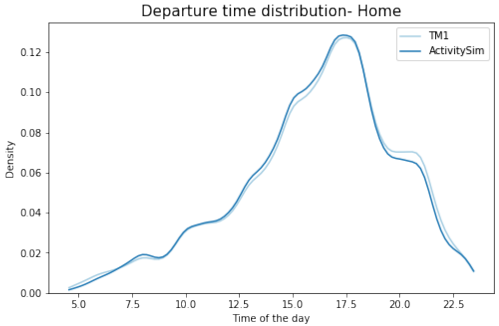
ACTIVITYSIM RESULTS

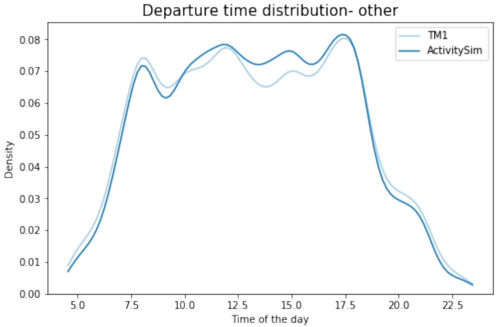
Validation – Departure Time

- Departure time distribution from ActivitySim closely matches Metropolitan Transportation Commission (MTC) travel model results for work and school trips



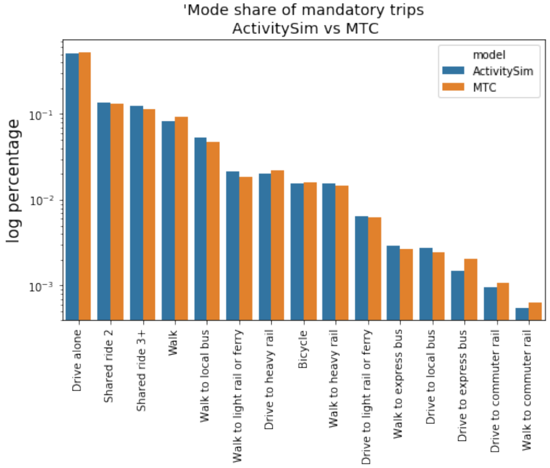


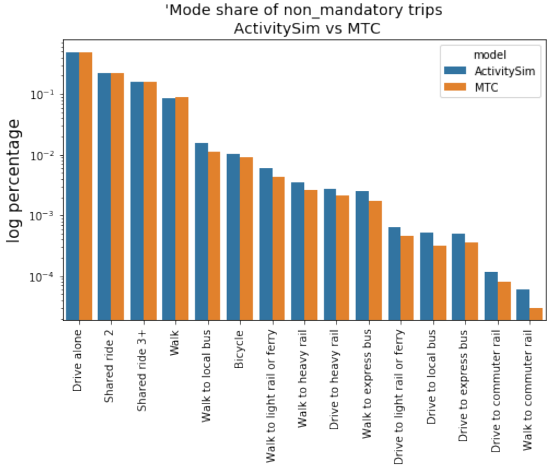




ACTIVITYSIM RESULTS

Validation – Mode share



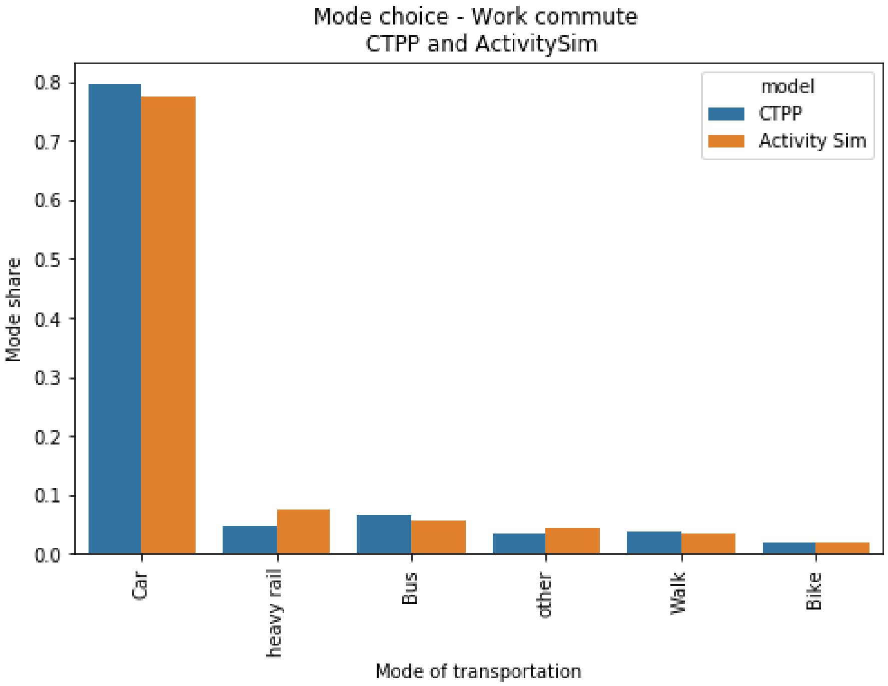


- **Mode shares from ActivitySim closely match MTC travel model mode shares for mandatory and non mandatory trips.**

ACTIVITYSIM RESULTS

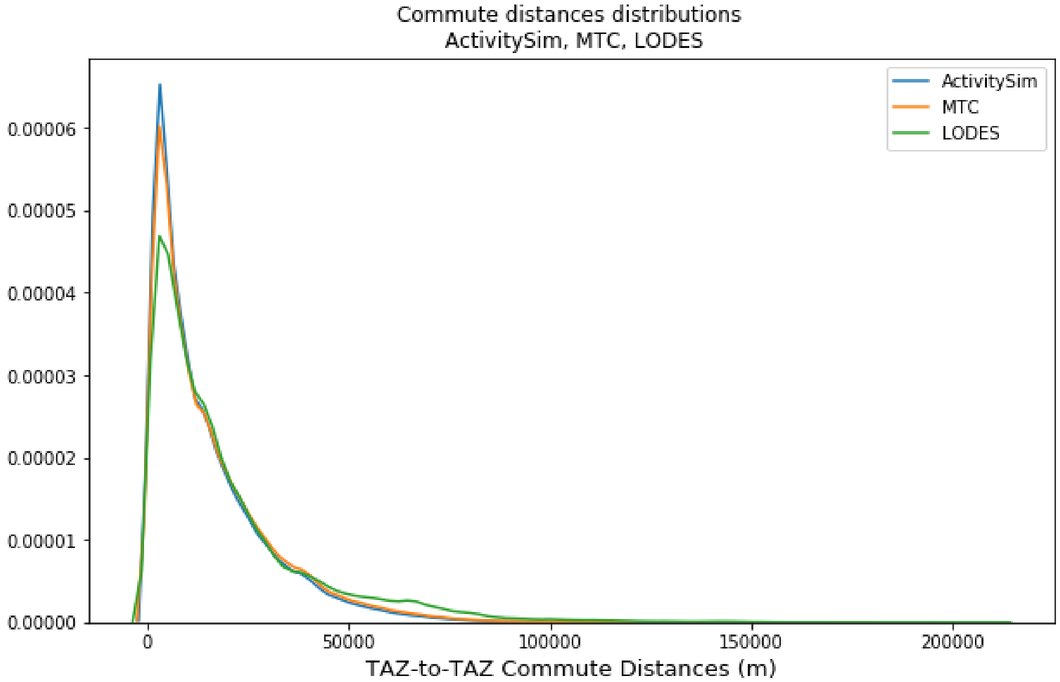
Validation – Mode share of commute trips

- Mode shares reasonable closr to Census Transportation Planning Package (CTPP) mode shares



ACTIVITYSIM RESULTS

Validation – Commute trips distance

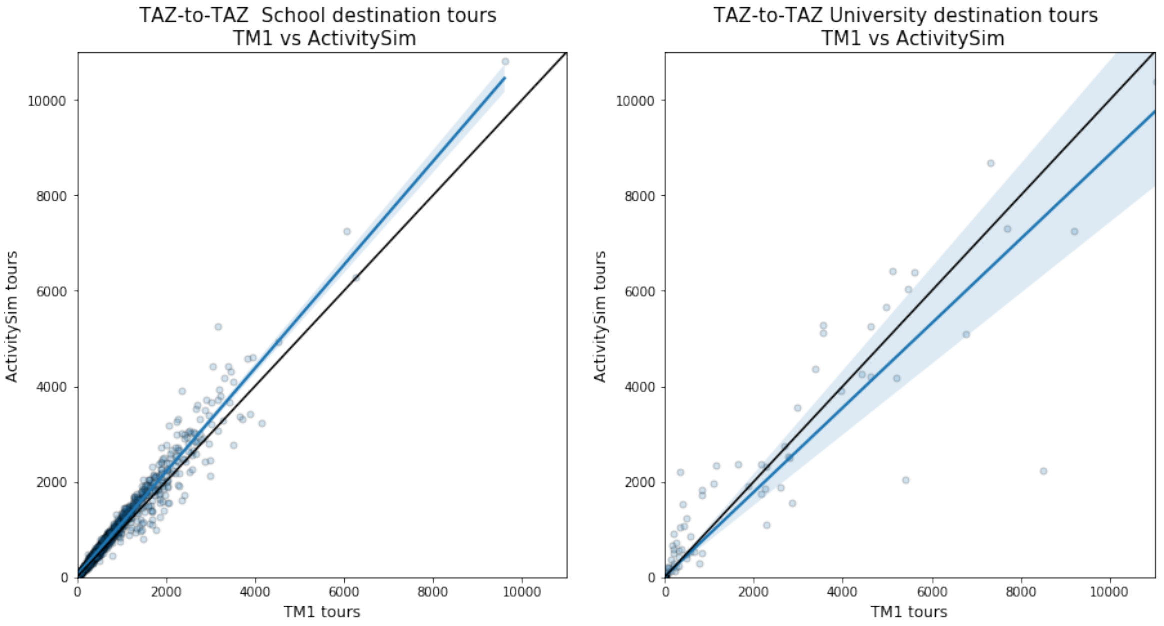


- **Commute distance distribution closely match MTC and the Longitudinal Employer-Household Dynamics (LEHD) database, Origin-DestinationEmployment Statistics.**

ACTIVITYSIM RESULTS

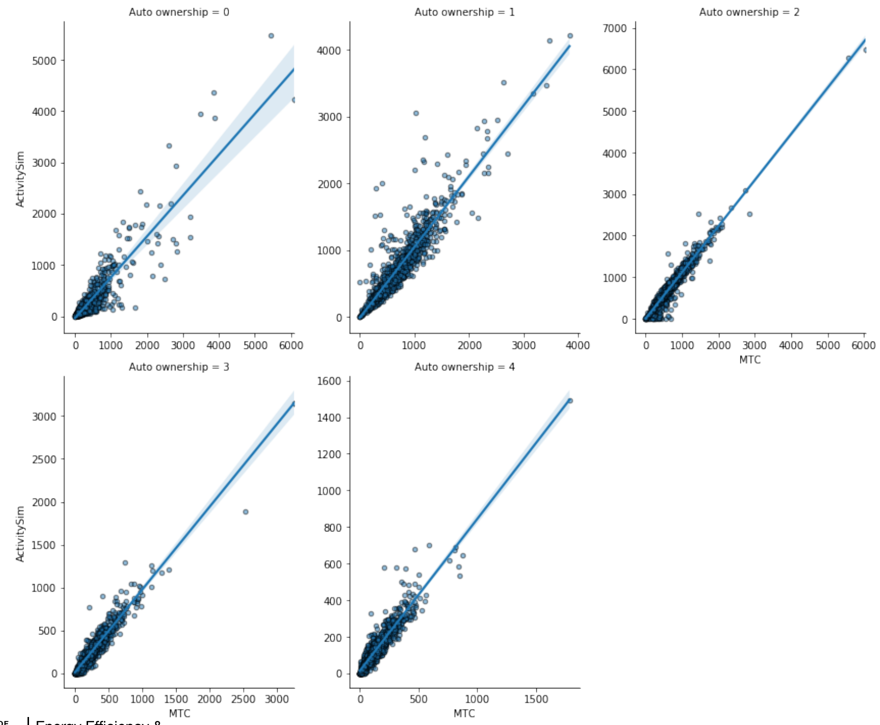
Validation – School Choice

- Zone to zone distributions for school destination choice models closely match MTC model results.



ACTIVITYSIM RESULTS

Validation – Auto-ownership model

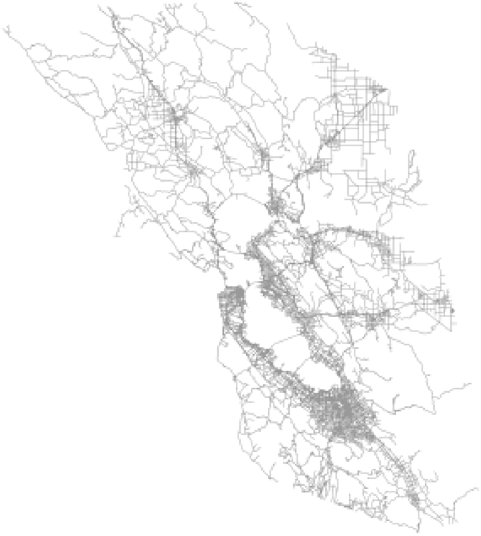


- **ActivitySim auto ownership model results closely match MTC model results**

TECHNICAL ACCOMPLISHMENTS

Traffic Microsimulation on a GPU to massively scale performance

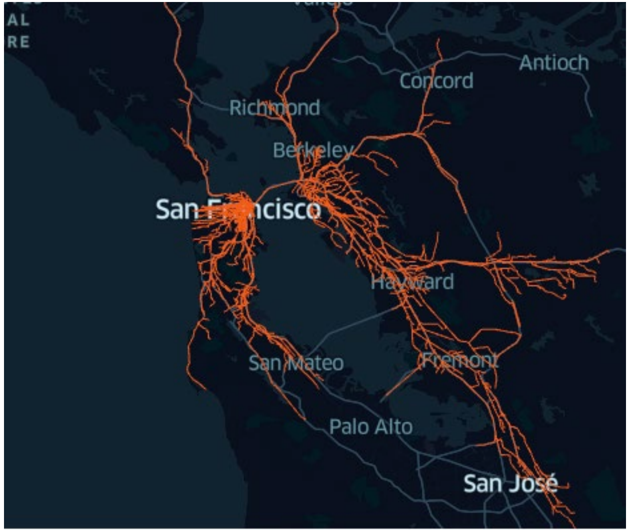
- Bay Area network (derived from OSM/OSMnx)
- 223K nodes
- 560K edges



O/D GENERATION

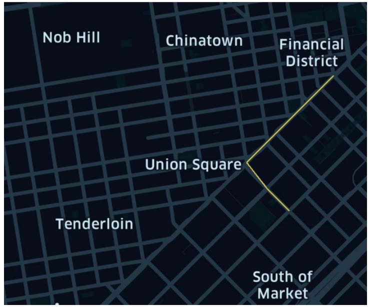
Static demand (now using activity-based demand from ActivitySim)

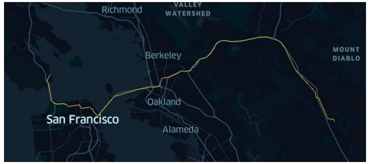
- Bay Area MTC data (2017)
- Pared down to morning travel, containing highest # of commuters
- TAZ <-> TAZ origin/destination data
  - Randomly assign nodes as O and D within the TAZs
- 3.1M total OD pairs between 5am-12pm

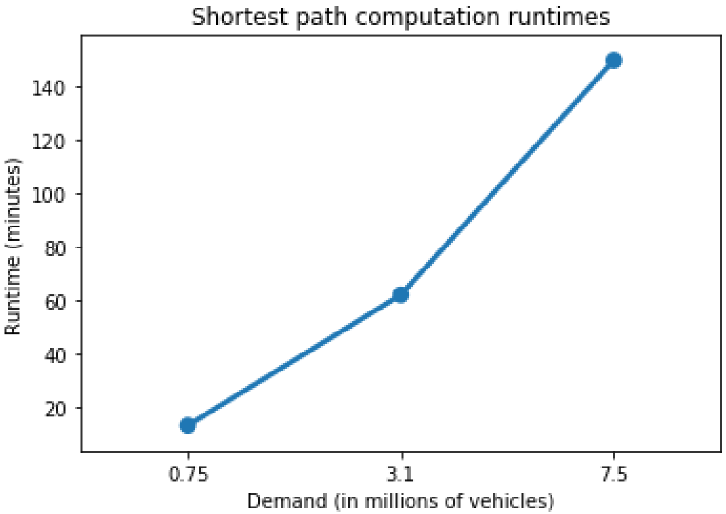


SHORTEST PATH

Parallelized priority queue



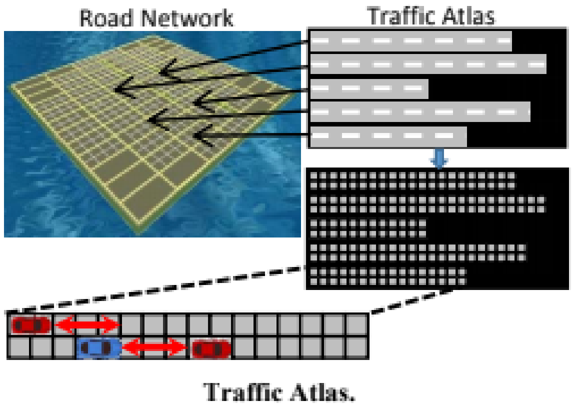




- Single source shortest path (SSSP) •Dijkstra priority queue greedily selects closest vertex that has not yet been processed
- Parallelized using OpenMP framework of message passing and shared memory usage

MICROSIMULATION

Governing dynamics



$$\dot{v} = a\left[1 - \left(\frac{v}{v_o}\right)^{\delta} - \left(\frac{s^*(v,\Delta v)}{s}\right)^2\right]$$

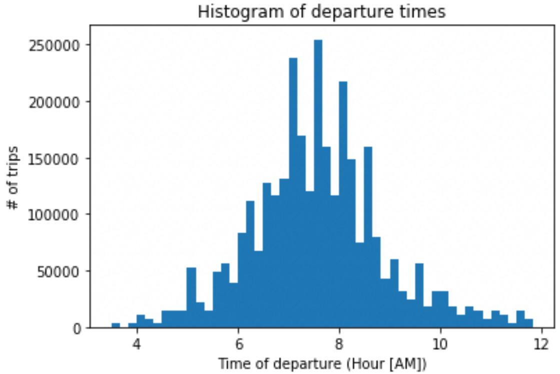
$$m_i = \begin{cases} \exp(-(x_i - x_0)^2) & x_i > x_0 \\ 1 & x_i \le x_0 \end{cases}$$

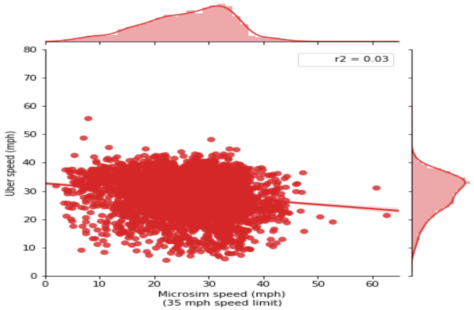
- 7 hours of simulation with .5 second timesteps
- Car-following, lane changing, and gap acceptance
- Parallelized, GPU-based using CUDA
- Vehicle checks the traffic atlas to find the position and speed of surrounding cars
- **~6.5 minute runtime** (massive speedup enabling metro scale microsimulation)

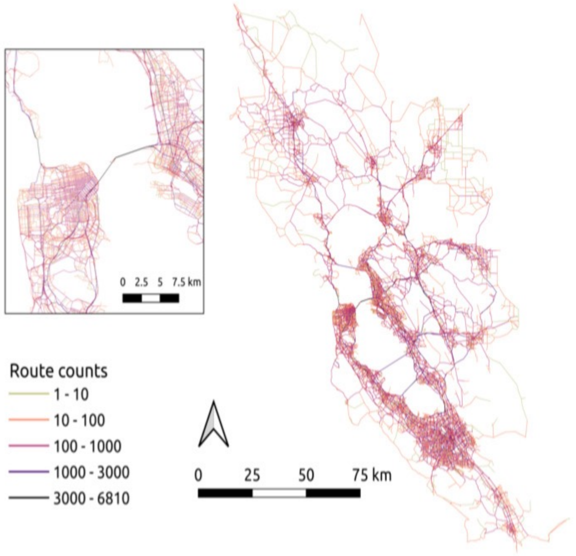
SIMULATION STATISTICS

Departure times, average speeds, and edge volumes

- Departure times currently based on Gaussian distribution
- Speeds follow normal and lognormal distributions, depending on edge speed limit
- Edge volumes reflect congestion on Bay Bridge, large corridors



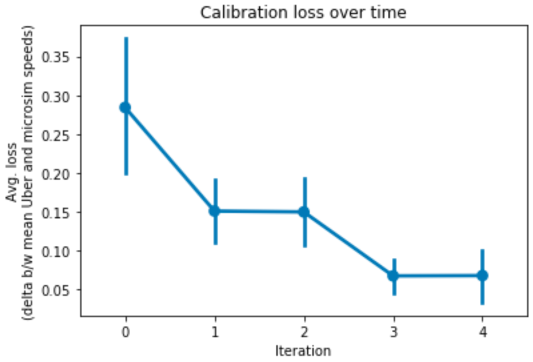




CALIBRATION

Minibatch gradient descent on four parameters

$$\min_{a,b,T,s_0} \sum_{n=1}^{N} \frac{\sum_{k=1}^{K} [a(1-(\frac{v_k}{v_{0,n}})^{\delta} - (\frac{s_o+Tv+\frac{v}{2\sqrt{ab}}}{s})^2]t}{K} - \overline{v}_{uber}|$$

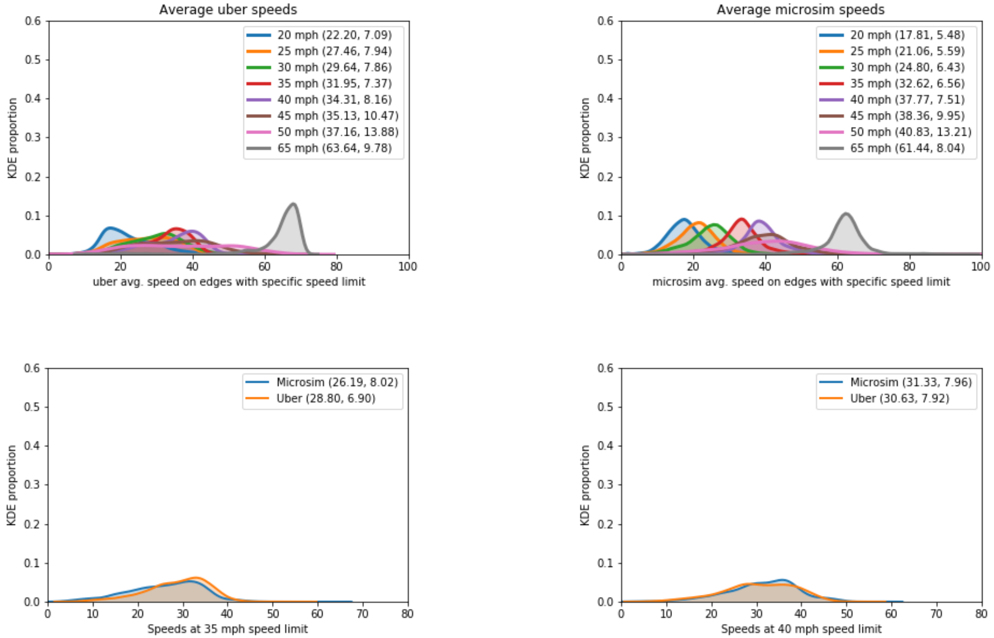


- Minibatch gradient descent within reasonable ranges of *a*, *b*, *T*, & s_0
- Batches of 5 random sets per iteration
- Threshold of .05 mph error for convergence
- Converges in 5 iterations

VALIDATION

Comparison to Uber Movement edge data per hour

- Closely match Uber movement speed data per edge, even with oversimplified intersection traffic controls
- Edge speed limit and Uber standard deviations (2x) used to model Uber distributions more closely



ONGOING ENHANCEMENTS

Real activity demand and dynamic shortest path

- Use real activity demand generated from ActivitySim models rather than synthetic MTC data with random departure times
- Update average edge speeds and probabilistically choose different paths
- Leverage subgraph characteristics to improve runtime
- Every subgraph OD has multiple trips between them and each trip chooses 1 out of 3 possible routes

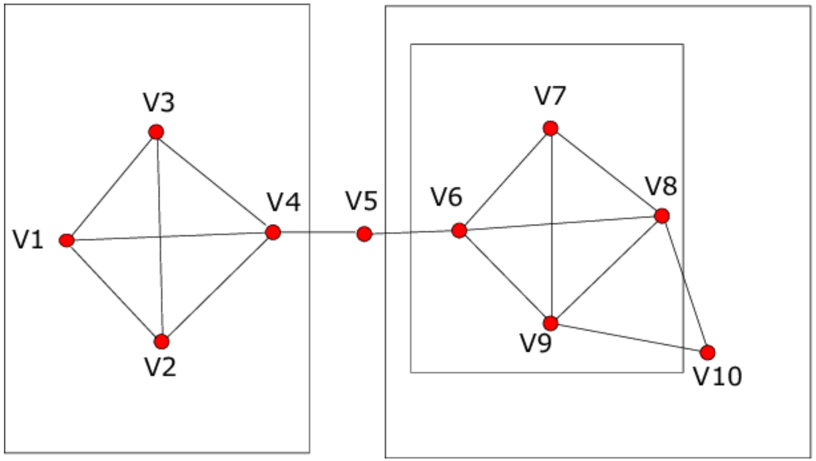
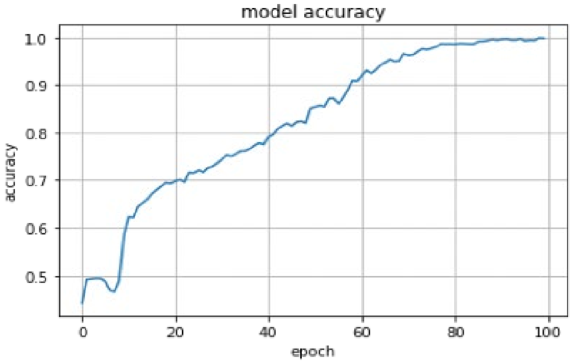


Image source: Top-k Overlapping Densest Subgraphs: Approximation and Complexity

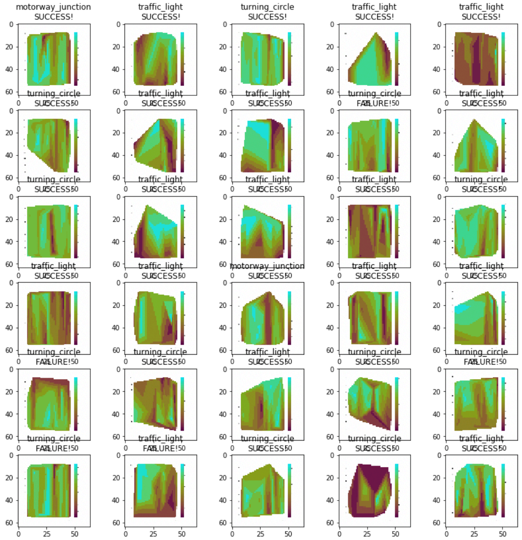
ONGOING ENHANCEMENTS (CONT'D)

Intersection modeling and control inference

- Compiled HERE trajectory data that contain speeds, timestamps, and locations every minute
- Gathered labels (though sparse) of certain intersections' traffic control from OSM
- Use labeled training data in supervised learning algorithm using CNN
- Apply trained neural network model to test data (whose labels exist) and determine accuracy



- Training accuracy - 99%
- Test accuracy - 72%



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MOBILITY FOR OPPORTUNITY

FOR MORE INFORMATION

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